Can/will climate change impact the wind energy industry?

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Why wind energy?

- Massive resource
  - 428 TW (cf. TPES 18 TW)
- Wind-Electricity production
  - World-wide 2-3% (IEA, 2013)
  - 4% US. 8% EU

- Major challenges:
  - Defining ‘target’ for skill assessment & algorithm training
  - For resource: Upper percentiles NEED to be right! $E \propto p_{90}$
  - For operating conditions: Extremes & complex variables (icing)

- Key parameters (for financing)
  - P50: AEP projected to be equaled/exceeded on 50% of years during wind farm operation.
  - P90: AEP that is associated with a 10% risk of not being reached.

\[
P(U) = 1 - \exp \left( - \frac{U}{A} \right)^k
\]

\[
E = \frac{1}{2} \rho A^3 \Gamma \left( 1 + \frac{3}{k} \right)
\]

$U_{50\text{th percentile}} \approx 7 \text{ ms}^{-1} \ (11\% \text{ of power})$

$U_{90\text{th percentile}} \approx 12.5 \text{ ms}^{-1} \ (75\% \text{ of power})$
Why might climate change impact regional wind resources/operating conditions?

- Largest resource & most turbines deployed in mid-latitudes
- In absence of thermotopographic forcing, spatio-temporal variability of resource
  \[ = f(\text{frequency & intensity & translational speed of transitory synoptic scale phenomena}) \]
  - Track = \( f(\text{equator-pole temperature gradient, temperature variance, teleconnections...}) \)
  - Translational speed = \( f(\text{jet stream wind speeds}) \)
  - Intensity =
    - \( f(\text{vertical stratification & momentum transport}) \)
    - \( f(\text{energy from condensation of water vapor}) \)

Annual frequency of cyclones (ERA-40) #/month per unit area (5°spherical cap)

Making wind projections: Climate modes

Teleconnections: Climate modes – wind:
Manifest across much of contiguous US & N. Europe
‘Significant’ (at least for p90)
Asymmetric w/index phase (mode-mode interactions?)

p90 wind speed under different index conditions. Positive/Negative: index > ±1.

Schoof & Pryor (2014): JGR
CMIP-5 climate modes

Schoof & Pryor (2014): JGR

Climate modes (ENSO, AO, PNA) from ESM: ?Good enough?
Making wind projections: Do LAM ‘added-value’?

Pryor et al. (2012a): JGR

Skill: Application of RCMs ‘adds value’: BSS v. NARR
> 0 for p90 & p95

Underestimation of inter-annual variability
Making wind projections: LAM variability

Wind climates from NARCCAP (@ 50 km):
Differences: RCM to RCM > LBC

Pryor et al. (2012a): JGR
Making wind climate projections: Resolution

Inc. resolution (even when mapped back to coarse resolution) adds value
Diagnostic power of time series analysis

* ≈ 70 m a.g.l.

Pryor et al. (2012b): JGR
Making wind projections: ESD

Transfer function
Surface parameter = $f$(descriptors of large scale climate)

AOGCM
Whole globe
Lower resolution

Probabilistic
Station specific
Weibull A & k
Input to transfer function from AOGCM

\[ A_i = c_1 \overline{PG_j} + c_2 \overline{\zeta_j} + c_3 \sigma(\zeta_j) \]
\[ k_i = c_4 \overline{PG_j} + c_5 \sigma(PG_j) + c_6 \zeta_j + c_7 \sigma(\zeta_j) + c_8 \]
ESD: Skill

\[ A_i = c_1 P G_j + c_2 \zeta_j + c_3 \sigma(\zeta_j) \]

\[ k_i = c_4 P G_j + c_5 \sigma(P G_j) + c_6 \zeta_j + c_7 \sigma(\zeta_j) + c_8 \]

Pryor & Barthelmie (2014): ERL

Skill v. independent data: Yes!
No value added by hybrid downscaling (predictors from 50 km v 200 km)
Making wind climate projections: extremes

\[
P(U_{\text{max}}) = \exp \left( -\exp \left[ -\frac{U_{\text{max}} - \beta}{\alpha} \right] \right)
\]

\[
U_T = \frac{-1}{\alpha} \ln \left[ \ln \left( \frac{T}{T - 1} \right) \right] + \beta
\]

\[\alpha, \beta = f(\mu, \sigma \text{ of } U_{\text{max}})\]

\[\alpha, \beta = f(A,k)\]

<table>
<thead>
<tr>
<th>1961-1990</th>
<th>Lat (N)</th>
<th>Lng (E)</th>
<th>(U_{50}) (ms(^{-1}))</th>
<th>95% C.I. (1.96(\sigma))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Westermarkelsdorf 1 (hr av)</td>
<td>54.55</td>
<td>11.1</td>
<td>26.62</td>
<td>3.69</td>
</tr>
<tr>
<td>HIRHAM5/ECHAM5 (hr av)</td>
<td>54.53</td>
<td>11.28</td>
<td>24.34</td>
<td>1.80</td>
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<tr>
<td>HIRHAM5/ERA-40 (hr av)</td>
<td>54.53</td>
<td>11.28</td>
<td>28.31</td>
<td>3.81</td>
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<tr>
<td>Probabilistic/ ECHAM5 (hr av)</td>
<td>54.57</td>
<td>12.33</td>
<td>26.40</td>
<td>1.63</td>
</tr>
</tbody>
</table>

HIRHAM at 0.22°) and probabilistic downscaling have skill for \(U_{50}\)!

GOAL: ‘Better’ (i.e. more robust and reliable) predictions of AEP P50 and P90 for risk reduction in wind farm financing

Approach 1: Machine learning tools linking climate modes & local AEP

Approach 2: Limited area models: WRF: Value added by enhanced res.

Approach 3: Adaptive grid model. Test viability

CMIP5 & CMIP6

NA-CORDEX

DIAGNOSTIC ATTRIBUTION OF SKILL